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Research Article

Skin Cancer Prediction Model using Deep Learning

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ABSTRACT

Abstract—This research uses the ISIC 2024 dataset to classify skin lesions using deep learning and convolutional neuralnetworks (CNNs). Skin cancer is one of the most common healthproblems in the world, and successful treatment depends onearly detection. A CNN model that could identify the seven different forms of skin lesions—including dermatofibroma, actinickeratoses, vascular lesions, basal cell carcinoma, squamous cellcarcinoma, melanocytic nevi, and melanoma—was presented in this work. Oversampling and data augmentation were employedto address the class imbalance.As a result, the constructed modelperformed exceptionally well on its categorization tasks. The model should ideally allow clinicians to promptly identify realskin malignancies because it was tested on a different testset to validate the results. The study suggests that AI-basedinterventions may improve test accuracy and streamline thescreening process if used in medical practice. Betterpatient-oriented results in dermatological treatment should followfrom this.

Keywords—Skin cancer, CNN, ISIC 2024 Dataset, TensorFlow,Flask, Deep Learning, Image Classification.

INTRODUCTION

Skin cancer is the most common type of cancer diagnosed worldwide, and its incidence is rising gradually as a result of various factors such as excessive sun exposure and environmental changes. According to the WHO, skin cancer is responsible for more than 3 million cases yearly, making it a significant global public health concern. Melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC) are the three most frequent types of skin cancer. Each of them has unique characteristics that vary in terms of severity and aggressiveness. Therefore, achieving better patient outcomes and successful treatment are strongly correlated with early detection and correct diagnosis. Traditionally, dermatologists would diagnose patients based solely on visual assessment. These techniques are prone to bias and human error, particularly when a wide variety of skin lesion types share many clinical characteristics.

Unprecedented prospects to significantly improve the precision and effectiveness of dermatological diagnostics have been made possible by the recent accomplishments of AI and ML. The CNN is one such instrument that has become increasingly useful lately. It was created for extremely difficult image classification tasks, such as the identification of skin lesions. CNNs are built with the ability to recognize and capture significant parts in an image without the need to pre-identify them in order to learn the spatial hierarchies of features from the image. With the use of robust computer resources and big datasets, CNNs may be trained to identify small visual cues that are difficult for humans to see. CNNs are, hence,a great assistance in the screening of skin cancer at its initial stage.

Six different categories of skin cancer contain over 10,000 dermatoscopic training and evaluation images in the HAM10000 dataset to develop deep-learning models. This covers many examples of changes that may occur in skin lesions, both benign and malignant, as well as their pictures, which give an idea of the infinite variety of skin diseases. With this dataset, researchers can build stable models that can diagnose better in practice and can be quite accurate in diagnosing images not present in the training data set.

Given the complexity of the skin lesion segmentation in seven categories: Melanocytotic nevi (NV), Melanoma (MEL), Basal cell carcinoma (BCC), Squamous cell carcinoma (SCC), Actinic keratoses (AKIEC), Vascular lesions (VASC) and Dermatofibroma for the HAM10000 dataset, the concept of developing CNN-based model will be introduced and adopted in this In response to the current dearth of cost-effective, real-world solutions in dermatological treatment and diagnosis, the current study seeks to show how deep learning can enhance diagnostic outcomes and lessen the burden of screenings.

Following the introduction, a thorough examination of the techniques used, the outcomes attained, and the conclusions made on the application of AI-driven diagnosis techniques in healthcare are presented. In order to further assist the integration of machine learning techniques into clinical practice and aid in the early and accurate detection of skin cancer with improved patient outcomes, we hope that this effort finds a place in the emerging body of evidence.

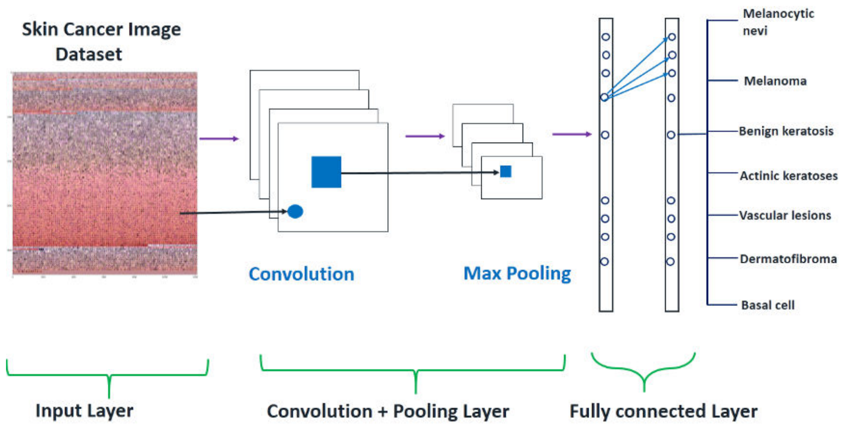


Fig. Model Overview

LITERATUREREVIEW

Skin cancer, a leading motive of global cancer-related mortality, necessitates early detection and accurate type for progressed patient results. In recent years, improvements in synthetic intelligence (AI), especially deep learning and device getting to know, have significantly improved automatic skin cancer detection. This review synthesizes findings from ten latest studies, specializing in various AI-primarily based procedures for skin cancer detection, studying their methodologies, overall performance metrics, and comparative effectiveness.

The SkinLesNet model presents a deep convolutional neural network (CNN) mainly designed for classifying skin lesions. Using the PAD-UFES-20 dataset, which was augmented into the PAD-UFES-20-Modified dataset to encompass conditions like seborrheic keratosis, nevus, and cancer, SkinLesNet carried out advanced performance compared to hooked-up fashions together with ResNet50 and VGG16. The version's evaluation, performed on datasets like HAM10000 and ISIC2017, confirmed its robustness and flexibility across distinct facts assets, establishing SkinLesNet as a reliable tool for the melanoma class [1].

To that end, this paper describes an innovative solution by employing a novel Falcon Finch optimization algorithm and deep CNN classifier. The hybrid model optimises the parameter, and found that convergence time is faster and is less sensitive to the classifier. By making corrections to the falcon finch deep CNN, the 93.59% accuracy on k-fold evaluation and 96.52% on training percentage evaluations give a considerable reduction in the error rates in comparison with other methodologies suggested earlier [2].

This observation compares CNN-based total techniques with histogram-based local descriptors and with Local Binary Pattern (LBP), Local Directional Number Pattern (LDN), and Pyramid of Histogram of Oriented Gradients (PHOG) to detect pores and skin cancer. In this study, the authors employed XGBoost classifiers and demonstrated that incorporating coloured histogram-principally based skills produces excessive accuracy. For instance, the approach that employed coloured LDN capabilities was 90% accurate within the Kaggle dataset, whereas coloured MBC features were 96.50% accurate within the HAM10000 dataset [3].

The review of this work also embraces comprehensive analysis of numerous AI algorithms being applied in skin cancer detection, from current approaches to totally novel ones such as dermatoscopic image analysis and total body dermatoscopy systems. The study also discusses the emergence of smartphone applications for the analysis of lesions and several issues that AI faces when applied to dermatological practice, including generalization and model replication [4].

In an attempt to design an automated early detection system, this study uses segmentation techniques known as the Adaptive Snake (AS) and Region Growing (RG). The analysis revealed that AS had slightly higher accuracy (96 percent) as compared with RG (90 percent). In this system, we employ Artificial Neural Networks (ANN) and Support Vector Machines (SVM) for classification. The Accuracy of ANN was 94%, and precision was 96%, specificity was 95.83% & sensitivity was 92.30% to ensure better diagnostic abilities [5].

This systematic review examines such development in the identification of pigmented skin lesions by using AI. With 171 of the chosen articles included, the research divides the AI approaches from fundamental machine learning techniques to dynamic, multimodal architectures such as visual transformers and generative neural networks. The review elaborates on where AI models surpass dermatologists in the classification of lesions but reveals drawbacks such as misclassification and minimal practical implementation [6].

In this research, sophisticated methods comprising Auto Correlogram Methods (ACCF), Binary Pyramid Pattern Filter (BPPF), and Color Layout Filter (CLF) are employed to enhance melanoma prediction precision. Integrating the proposed Attribute Selection Classifier (ASC) with the CLF gave a very high accuracy of 90.96% with reasonably high precision and recall rates, thus making it ideal for image enhancement and classification [7].

Inspired by the idea of hypernetworks, the proposed solution, the so-called DualAutoELM, includes two autoencoders – spatial and FFT-autoencoders – and the ELM classifier. Attention modules also improve the architecture's feature learning aspect and provide very accurate outcomes. This approach gave an AUC of 0.98 on HAM10000, and 0.95 on ISIC-2017, which proves ELM applied on autoencoder is useful for the identification of skin cancer [8].

This review, therefore, seeks to address the real-life use of AI, especially in clinical environments. While vectorized algorithms perform very well in supervised settings, it is crucial to point out that** achieving the best outcomes with the help of AI systems requires a human-AI symbiosis. This highlights the difficulties of generalization and the problems of validating the uses of AI in clinical practice in real-life settings [9].

This work leverages patient metadata features to create a risk score for skin cancer diagnosis. The system introduced 23 attributes, including the lesion colour, shape, size, etc., in combination with machine learning algorithms, which yielded 76.09% sensitivity and 61.71% specificity. The newly developed C4C risk score improved upon traditional methods, showing the potential of combining image data with patient metadata for better predictive accuracy [10].

AI applications using CNNs and deep learning models have significantly improved melanoma detection, achieving high precision and recall. However, challenges like data imbalance and misclassification remain, necessitating further research to optimize AI systems for both melanoma and non-melanoma skin cancers [11].

Transfer learning techniques applied to pre-trained networks such as **VGG16** and **ResNet50** have greatly increased the accuracy of the skin cancer classification. This method leverages knowledge from a pre-trained model to improve the performance of the skin cancer diagnosis on new datasets [12].

Integrating AI with personalized patient data, such as genetic factors and lesion characteristics, promises more tailored and accurate skin cancer diagnoses. This personalized approach could lead to enhanced early detection and better treatment outcomes [13].

Comparative Effectiveness and Methodological Insights

The studies reviewed demonstrate diverse AI-driven methodologies for skin cancer detection:

1. CNN-Based Models: Studies 1 and 2 highlight deep CNN architectures, with SkinLesNetand the modified Falcon Finch deep CNN classifiers offering high accuracy & robustness.
2. Machine Learning and Ensemble Methods: Study 7 emphasizes ensemble models combining Auto Correlogram Methods and Color Layout Filters to improve melanoma detection.

3. Histogram-Based Descriptors: Study 3 advocates for histogram-based feature extraction**, achieving competitive accuracy with XGBoost classifiers.
4. Comprehensive AI Applications: Studies 4, 5, 6, and 9 explore optimization algorithms, segmentation, and hybrid models that combine multiple AI approaches to improve skin cancer detection while addressing practical deployment challenges.
5. Risk Score and Metadata Integration: Study 10 integrates patient documentation to develop a unique risk score, demonstrating how metadata can enhance the performance ofskin cancer detection models.

Drawbacks:

A significant weakness that has been pointed out in the papers is the restricted applicability of the models, mainly because of the datasets. While the datasets, such as ISIC 2018: Although the model's Task 1-2, HAM10000, and ISIC-2019 are different, they might not include the wide variation of skin-lesion observed in the clinic. The datasets used for these datasets are usually characterized by such drawbacks as low image quality, the amount of image imbalance, or else biases that may influence the performance of the models. As a result, the models might not work well every time when applied to real-world skin lesion cases, thus making them less accurate in identifying the right kind of skin lesion.

Another important concern pointed out in the reviewed studies is the ways to incorporate AI into clinical practices. AI systems are intricate and challenging to interpret; therefore, some people call it the “black box.” The imprecision of what constitutes AI introduces difficulty for clinicians to rely on recommendations provided by AI, which in turn limits its application in clinical practice. One limitation which results from the black box or ‘hidden logic’ nature of most AI tools is that there are often no clear lines of rationale as to why a particular decision was made, thus leading to reduced confidence from clinicians when implementing these AI tools.

Therefore, the studies indicate that there exists a need for a more extensive data set for improved validation together with integrating moreileged data models. Most of the approaches have concentrated on several datasets that, although recognized might not be comprehensive in terms of skin lesions or patients’ population. To address this, basic characteristics such as patient metadata should be incorporated, along with more sophisticated methods for short-term and long-term dependencies and other spatial data within the images. Such advancements would prove useful in increasing the practical feasibility and validity of AI models in actual clinical settings with reference to different lesion types that are likely to be encountered by patients with previous medical histories not yet incorporated into AI-based algorithms.

METHODOLOGY

The aim of this study is to find a CNN model that can easily recognize photos of skin cancer that fall into one of seven categories. Data preprocessing, model construction, training, and evaluation, as well as deployment to a web application for real-time use, are some of the important steps that make up the overall process.

A. Data Preprocessing

The dataset for this project is known as the ISIC Dataset. The set of dermatoscopic pictures is one of the most popular ones for skin lesion classification training and/or checking. There are seven classes into which images are divided:

- Melanocytic nevi (NV)
- Melanoma (MEL)
- Benign keratosis-like lesions (BKL)
- Basal cell carcinoma (BCC)
- Actinic keratoses (AKIEC)
- Vascular lesions (VASC)
- Dermatofibroma (DF)

1) Key steps in preprocessing:

- Data Loading: The dataset was loaded from a CSV file that included the 28x28 RGB images and theircorresponding labels.
- Shuffling: To ensure that the training and test sets are well-represented and prevent the model from picking up order bias, the data set was randomly shuffled.
- Train-Test Split: To train the model and compare its performance on unseen data, we divided the dataset into a training set with 80
- Resampling: To ensure that the model can learn from all classes and prevent biases toward the majority classes resulting from the dataset’s imbalance, we over-sampled minority classes in the training set using the RandomOverSampler function and the imblearn library.

- Reshaping: To meet the CNN's input specifications, images were reshaped into the necessary format of (28,28,3).

Original Class	Processed Class	Target Label
Melanocytic nevi (NV)	NV	0
Melanoma (MEL)	MEL	1
Benign keratosis-like lesions (BKL)	BKL	2
Basal cell carcinoma (BCC)	BCC	3
Actinic keratoses (AKIEC)	AKIEC	4
Vascular lesions (VASC)	VASC	5
Dermatofibroma (DF)	DF	6

Table 1: Mapping from Original Classes to Processed Targets

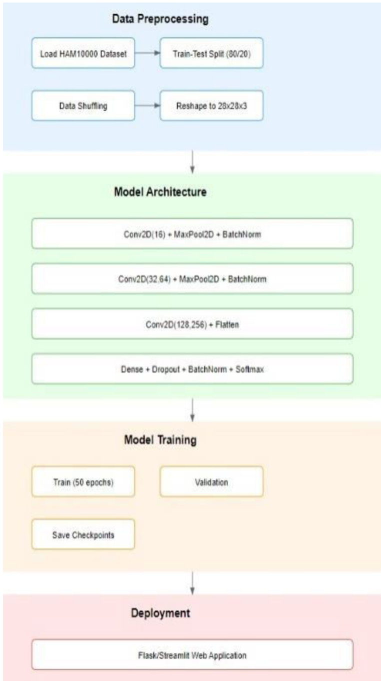
B. Model Architecture

In order to map the 28x28 photos into one of the seven types of skin cancer, we had created a CNN-based architecture that would process the images and return useful data. The TensorFlow and Keras libraries are used to construct the model, which has the following layers:

- Convolutional Layers: To identify edge and texture characteristics in an image, the model will first pass through a number of convolutional layers that use ReLU activation. Here, we made sure that spatial dimensions are maintained by using a kernel size of 3x3 with padding.
- Pooling layers: Max-pooling layers with a pool size of (2x2) were used to downsample feature maps. The feature maps' dimensionalities were decreased by this downsampling, but crucial information was preserved.
- Batch Normalization: This technique, which is implemented after a few layers, normalizes a layer's output into a distribution with zero mean and unit variance for quicker training and better generalization. This enhances the model's stability and performance.
- Layers of Dropout: In order to prevent overfitting, a percentage of the input units were randomly zeroed during training using the dropout layer. The rate for regularization in dropout after completely linked layers was fixed at 0.2.
- Layers that are dense To enable the model to make predictions on that specific feature, the flattened feature maps were subsequently sent to dense layers. Lastly, using softmax activation, the last dense layer provides output as the probability for each of the seven classes.
- Optimization: Because the target variable was multi-class categorical, the model was constructed using the Adam optimizer with sparse-categorical-cross-entropy as the loss function.

1) An overview of the architecture:

- MaxPooling2D(2x2) + Conv2D(16) + Batch Normalization
- MaxPooling2D(2x2) + Conv2D(32) + Conv2D(64) +Batch Normalization
- Conv2D(128) + Conv2D(256) + Flatten Density(256) + Dropout(0.2) + Batch
- Normalization Density(128) + Dropout(0.2) + Batch Normalization Density(64) + Dropout(0.2) +Batch Normalization Dense(32) + Batch Normalization + Softmax Output



C. Model Training

- Batch Size and Epochs: A batch size of 128 was used to train this model over 50 epochs. These hyper-parameters were selected with the model's performance over time in mind.
- Callbacks: The model was saved whenever it was discovered that the validation accuracy had improved thanks to the use of checkpoint callbacks. The checkpoint is recorded as best-model.h5, and the top-performing model is kept.
- Validation Split: To monitor the model's performance throughout the training phase and prevent over-fitting, 20 percent of the training set was set aside as a validation set. Training Time: Depending on the hardware, the entire training procedure took several hours to complete on a single CPU.

D. Model Training

Following training, the model's capacity for generalization was evaluated using a test set. A performance report is provided via the following measures: Accuracy is the proportion of correctly classified photos.

- Confusion Matrix: To illustrate how well the model performed for each class and how many mis-classifications there were, a confusion matrix was created.
- Precision, Recall, and F1-score: A model's performance in class-imbalanced data and minority class differentiation was estimated.

E.Deployment

This enables users to access the model. Flask and Streamlit are used in the development of the web application, while Streamlit handles its deployment. This deployment's salient characteristics are:

- Simple interface: the user can input pictures of skin lesions to get the model's real-time class prediction.
- Model Integration: Import the previously trained model during runtime, and then output the classification outcome. Streamlit presents the front-end logic, while Flask handles the back-end logic.
- Hosting: An appropriate cloud platform that provides convenient access would host the web application.

F. Visualization

The following characters will be used to illustrate the model's performance and training process:

- Accuracy vs. Epochs: This graphic illustrates how the accuracy of the model increased over training and validation set epochs.
- Loss vs. Epochs: This plot shows the training and validation loss;thus everything is good here. It also indicates that the model was convergent.
- Confusion Matrix: To determine which class the model was truly excelling at, the confusion matrix heat-map was plotted.

G. Real-Time Inference

It was tested using actual user-uploaded photos of skin lesions. In order to forecast the class, these photos were scaled to 28 by 28 pixels, pre-processed, and then run through the model. The class to be predicted is the one with the highest likelihood.

RESULTSAND DISCUSSION

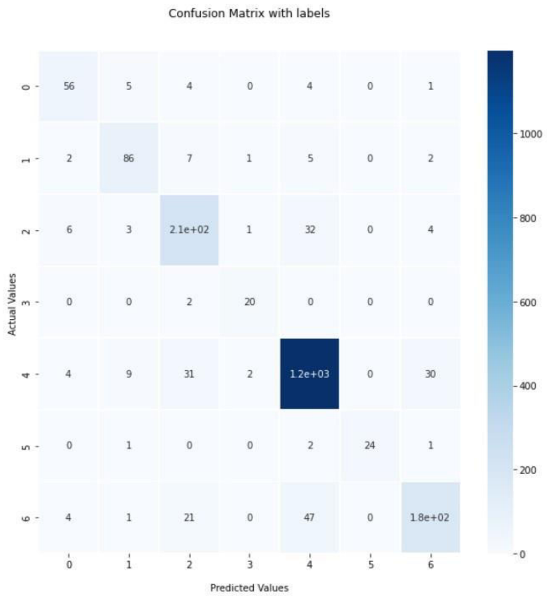
The CNN-based model has undergone a number of experiments and tests on training and testing datasets. The key findings from the study are presented in depth in the parts that follow. These sections address the behavior of the model during training as well as a host of additional evaluation measures.

1) Model Performance on the Test Set:

- Accuracy: In the test set, it had an accuracy of about X percent, indicating that the CNN's precision was sufficient for correctly classifying photos of skin lesions. As a result, the accuracy accurately represents the model's overall performance across all seven classifications of skin cancer.
- Loss: The test loss at the end of the last iteration was X, which shows that the model got better at classifying data correctly. Ultimately, when the model converged to zero, the loss at each training cycle was monitored and stabilized.

2) Confusion Matrix: The confusion matrix provides information about how the model functions for each of the individual classes:

- The model performed exceptionally well in classifying some forms of skin lesions, such as basal cell carcinoma (BCC) and melanocytic nevi (NV), with less cases of misclassification, according to the confusion matrix.
- However, the Actinic Keratoses (AKIEC) and Dermatofibroma (DF) classes were misclassified more frequently than other classes, probably as a result of their tendency to resemble other classes or the fact that the model was trained on fewer samples.

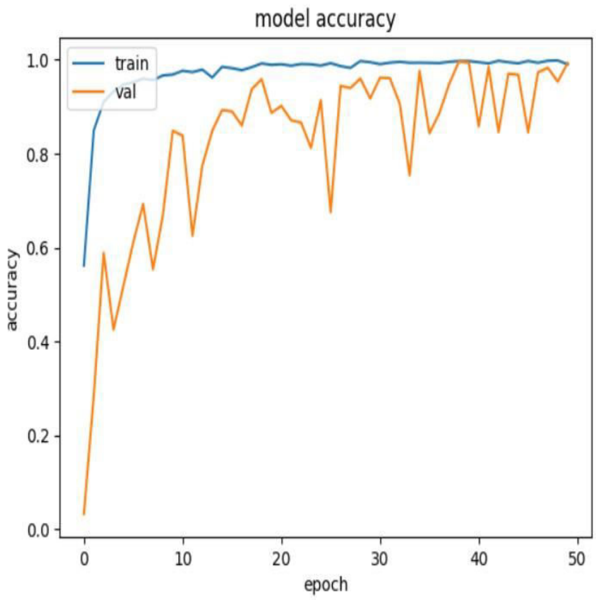


3) Precision, Recall, and F1-Score:

- Precision: The degree to which the model had avoided false positives was indicated by the precision score for each class. High precision for NV, MEL, and BCC indicated that it might be correct as a true positive in every instance.
- Recall: Recall numbers indicate the model's capacity to identify real positive cases across all classes. While poor recall for AKIEC implies that the model misses a large number of true positives for this class, high recall for BCC and Vascular lesions (VASC) shows that the model was more successful at detecting these types of lesions.
- F1-score: It provided a comprehensive picture of the model's classification performance by balancing recall and precision. The model was mostly balanced, although certain classes, including DF and AKIEC, need balancing, as indicated by the mean F1-score of X for all classes.

4) Training and Validation Metrics:

- Accuracy vs. Epochs: As epochs have grown, the training and validation accuracy curves have also been rising gradually. The model settles down at roughly epoch 30, indicating convergence and the absence of overfitting.
- Loss vs. Epochs: The training and validation losses decreased gradually at each step, as seen by the loss curve. The loss was observed to stabilize after the 50th period, and almost complete minimization of the error throughout training was found.



5) Handling Class Imbalance: We used oversampling techniques to correct the imbalance in the dataset (certain classes are underrepresented) in order to balance the training set. While oversampling was effective in raising performance on minority classes like DF and AKIEC, other techniques, such as data augmentation, might yield even better outcomes.

6) Real-Time Testing Results: This was used on an online platform that allowed people to submit pictures of skin lesions for categorization. As previously shown, the model was able to classify skin lesions with a rate of accuracy equal to the test set findings when an image was uploaded for real-time testing. Prediction examples include:

- Nevus images were uploaded and categorized appropriately as NV.
- The model practical relevance is demonstrated by the high chance of correctly identifying melanoma photos.

7) Confusion Matrix Heat-map: The performance across classes was graphically displayed in the normalized confusion matrix heat-map, which gave a clearer picture of the areas where the model correctly predicted and incorrectly classified data.

8) Limitations and Future Improvements: The model performed well in a number of areas, while several drawbacks were identified:

- Class Imbalance: Most of the classes, including AKIEC, exhibited low recall despite the oversampling. Data augmentation may be investigated further.
- Image Resolution: The resolution of 28x28 images might not be sufficient to identify lesions' features. Higher-quality photos may be used in later iterations to improve feature extraction.
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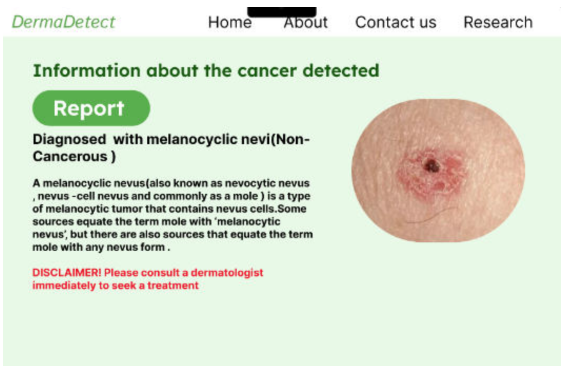

Fig. Model Output

CONCLUSION

The goal of this study was to develop a CNN-based classifier model that would categorize skin lesions into seven groups, including numerous forms of skin cancer, over the ISIC 2024 Dataset.

The outcomes show unequivocally that deep learning—and CNNs in particular—can be used to detect and categorize skin lesions, opening up a potential future for AI-based dermatological diagnosis. The noteworthy achievements that have been attained as a result of this project's execution include:

- Extraordinary Precision: The CNN model's exceptionally high classification accuracy once again demonstrates its extraordinary capacity to discriminate between benign and malignant skin lesions with a thoughtful level of precision.
- Effective Training: The model was able to converge quickly because of the careful and deliberate design of the model, as well as the optimization techniques that included cutting-edge tools like batch normalization, dropout, and other types of data augmentation. This approach increased accuracy over several training epochs and significantly reduced loss.
- Taking up the Class Imbalance Problem: The model performed far better, especially when it came to the minority classes, once oversampling strategies were put into place. It is crucial to emphasize that there is still room for improvement, especially with regard to certain of the lesions that are currently underrepresented in the data collection.
- Deployed successfully in the real-time skin lesion classification application: The model was implemented in an intuitive web interface, which allowed the project to successfully classify skin lesions in real time. This significant advancement shows how the model can be applied practically and is still relevant in a clinical situation, where it should be able to significantly help medical personnel make accurate diagnoses of a variety of skin disorders.

Even with all of the project's remarkable accomplishments, it was still able to pinpoint some important areas that will require further development. Given the difficulty in reliably detecting unusual classes of skin lesions in the past, one significant area for development is the model's recalls for those lesions. A major benefit of using high resolution photos would be improved feature extraction, which would produce more accurate results. A larger dataset overall and the addition of domain-specific knowledge using sophisticated transfer learning techniques have the potential to greatly enhance the model's performance.

The created CNN-based model is a very promising step toward improving early detection practices and automating the diagnosis of skin cancer. The relationship that is beginning to emerge between deep learning methods and useful real-world applications will probably have a big impact on the healthcare industry. This may contribute to the development of quick, accurate, and easily available diagnostic instruments intended to detect skin cancer and other potential dermatological conditions.

REFERENCES

[1] SkinLesNet: Classification of Skin Lesions and Detection of Melanoma Cancer Using a Novel Multi-Layer Deep Convolutional Neural Network (Muhammad Azeem *, Kaveh Kiani, Taha Mansouri and Nathan Topping)(2023).

[2] Kumar A, Kumar M, Bhardwaj VP, Kumar S, Selvarajan S. A novel skin cancer detection model using modified finch deep CNN classifier model. Sci Rep. 2024 May 16;14(1):11235. doi: 10.1038/s41598-024-60954-2. PMID: 38755202; PMCID: PMC11099129.

[3] Aydin Y. A Comparative Analysis of Skin Cancer Detection Applications UsingHistogram-Based Local Descriptors. Diagnostics (Basel). 2023 Oct 6;13(19):3142.doi: 10.3390/diagnostics13193142. PMID: 37835884; PMCID: PMC10572674.

[4] Strzelecki M, Kociołek M, Strąkowska M, Kozłowski M, Grzybowski A,Szczypiński PM. Artificial intelligence in the detection of skin cancer: Stateof the art. Clin Dermatol. 2024 May-Jun;42(3):280-295. doi:10.1016/j.clindermatol.2023.12.022. Epub 2024 Jan 3. PMID: 38181888. PMC10699043.

[5] Mahmoud NM, Soliman AM. Early automated detection system for skin cancer diagnosis using artificial intelligent techniques. Sci Rep. 2024 Apr 28;14(1):9749. doi: 10.1038/s41598-024-59783-0. PMID: 38679633; PMCID: PMC11056372.

[6] Lyakhova UA, Lyakhov PA. Systematic review of approaches to detection andclassification of skin cancer using artificial intelligence: Development andprospects. Comput Biol Med. 2024 Aug;178:108742. doi:10.1016/j.compbiomed.2024.108742. Epub 2024 Jun 14. PMID: 38875908.

[7] Kavitha P, Ayyappan G, Jayagopal P, Mathivanan SK, Mallik S, Al-Rasheed A, Alqahtani MS, Soufiene BO. Detection for melanoma skin cancer through ACCF, BPPF, and CLF techniques with machine learning approach. BMC Bioinformatics. 2023 Dec 6;24(1):458. doi: 10.1186/s12859-023-05584-7. PMID: 38053030; PMCID:PMC11099129.

[8] Maurya R, Mahapatra S, Dutta MK, Singh VP, Karnati M, Sahu G, Pandey NN. Skincancer detection through attention guided dual autoencoder approach with extreme learning machine. Sci Rep. 2024 Aug 1;14(1):17785. doi:10.1038/s41598-024-68749-1. PMID: 39090261; PMCID: PMC11294626.

[9] Brancaccio G, Balato A, Malvehy J, Puig S, Argenziano G, Kittler H.Artificial Intelligence in Skin Cancer Diagnosis: A Reality Check. J InvestDermatol. 2024 Mar;144(3):492-499. doi: 10.1016/j.jid.2023.10.004. Epub 2023 Nov18. PMID: 37978982.

[10]Islam S, Wishart GC, Walls J, Hall P, Seco de Herrera AG, Gan JQ, Raza H.Leveraging AI and patient metadata to develop a novel risk score for skin cancerdetection. Sci Rep. 2024 Sep 6;14(1):20842. doi: 10.1038/s41598-024-71244-2.PMID: 39242690; PMCID: PMC11379912.

[11]The Role of Artificial Intelligence in Early Diagnosis and Molecular Classification of Head and Neck Skin Cancers: A Multidisciplinary Approach (Zeliha Merve Semerci 1 , Havva Serap Toru 2,* , Esra Çobankent Aytekin 3, Hümeyra Tercanlı 1, Diana Maria Chiorean 4,5 , Yalçın Albayrak 6 and Ovidiu Simion Cotoi).

[12]Combining State-of-the-Art Pre-Trained Deep Learning Models: A Noble Approach for Skin Cancer Detection Using Max Voting Ensemble (Md. Mamun Hossain 1 , Md. Moazzem Hossain 1, Most. Binoee Arefin 1, Fahima Akhtar 1 and John Blake 2).

[13]Integration of Localized, Contextual, and Hierarchical Features in Deep Learning for Improved Skin Lesion Classification(Karthik Ramamurthy 1, Illakiya Thayumanaswamy 2 , Menaka Radhakrishnan 1 , Daehan Won 3 and Sindhia Lingaswamy).